Price Regulation in Secondary Insurance Markets*

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Abstract

Secondary life insurance markets are growing rapidly. From nearly no transactions in 1980, a wide variety of similar products in this market has developed, including viatical settlements, accelerated death benefits, and life settlements and as the population ages, these markets will become increasingly popular. Eight state governments, in a bid to guarantee sellers a "fair" price, have passed regulations setting a price floor on secondary life insurance market transactions, and more are considering doing the same. Using data from a unique random sample of HIV+ patients, we estimate welfare losses from transactions prevented by binding price floors in the viatical settlements market (an important segment of the secondary life insurance market). We find that price floors bind on HIV patients with greater than 4 years of life expectancy. Furthermore, HIV patients from states with price floors are significantly less likely to viaticate than similarly healthy HIV patients from other states. If price floors were adopted nationwide, they would rule out transactions worth $484 million, representing a welfare loss of $242 million per year.

I. INTRODUCTION

Secondary life insurance markets are growing rapidly. From nearly no transactions in 1980, a wide variety of similar products in this market has developed, including viatical settlements, accelerated death benefits, and life settlements. The American Council of Life Insurance (1998) reports that over $10 trillion in life insurance contracts (78% of all life insurance dollars) are held by companies that offer accelerated death benefits. These markets are likely to be increasingly important, as they attract the eldely, the frail, the disabled, and the HIV positive. Anyone who undergoes an unexpectedly large health shock after buying a life insurance policy will have an incentive to cash out—see Bhattacharya, Goldman, and Sood (2001). As the population ages, these markets will become increasingly popular. Indeed, Congress recently passed the Health Insurance Portability and Accountability Act, which exempts proceeds from secondary life insurance transactions from federal income taxes.[1] Yet there has been no serious economic analysis of these markets.

There has been increasing pressure to regulate this industry, spurred in part by recognition that one of the parties to the transaction is exceptionally vulnerable—that is, terminally-ill patients or the elderly. The National Association of Insurance Commissioners (NAIC) has issued model legislation as guidelines for state regulators. At present, 26 states have passed legislation covering viatical settlements and accelerated death benefits, many using the NAIC model.[2] The settlement price will depend on the health of the consumer. Thus, the minimum settlement ratios set by regulation depend on the life expectancy of the policyholder and the credit rating of the insurer. Not surprisingly, these are controversial. The viatical settlement industry argues that the minimum payments rule out certain settlements that are otherwise appropriate, thereby distorting the market.

A typical transaction in a secondary life insurance market works this way: the policyholder gets an immediate up-front payment at a discount to the face value of the life insurance; in return, he makes a third party (sometimes the life insurance company

[1] Health Insurance Portability and Accountability Act of 1996, U.S. PL 104-191.

itself in the case of accelerated death benefits) the sole beneficiary of the policy. It is important to recognize that the initial payout depends on the life expectancy of the policyholder, since the company collects the full value only when the patient dies.

This paper focuses on an important segment of the secondary life insurance market—viatical settlements. The viatical settlement industry emerged in 1989 in response to the AIDS epidemic. Beneficiaries with advanced HIV disease faced very high medical expenses as new treatments emerged. To finance this medical care, many considered the sale of their life insurance policies. By 1991 an estimated $50 million of viatical settlements were sold. The industry has been growing rapidly since then with $500 million in policies viaticated by 1995 and $1 billion in policies viaticated by 1998.[3]

Competitive models of price regulation predict that producers will supply less and consumers will have excess demand when binding price ceilings are imposed. A similar story holds for binding price floors, although there the problem is one of excess supply. This basic tenet of microeconomics implies that price regulation has a very circumscribed role, although policy makers often use them to ensure that consumer receive a "reasonable" price in new markets. We use a standard competitive model for pricing viatical settlements to estimate the welfare effects of new price regulations in the life insurance market designed to protect sick individuals who are considering selling their life insurance policies. We confirm these findings using a unique longitudinal database on HIV patients receiving care in the US.

II. PRICING OF VIATICAL SETTLEMENTS

As in all markets for mortality contingent contracts, viatical settlement firms need to know the health of consumers to construct price offers. Typically these firms use the services of in-house staff, independent physicians, actuaries and other consultants to determine the mortality risks of potential consumers before making a price offer.[4] The price firms are willing to pay will also depend on the cost of funds for viatical settlement

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[2] National Association of Insurance Commissioners, Advisory Package on Viatical Settlements. (1999).
[3] National Viatical Association, NVA Information Booklet, (1999).
[4] See note 1, *supra*.

firms. As one might expect, the price firms are willing to pay for a policy increases with the mortality risk of the consumer and decreases with the cost of funds for the firm. In the next section we show a simple model for deriving the price of a life insurance policy in a perfectly competitive market given the mortality risk of the insured and the cost of funds for viatical settlement firms.

Let $a = (a_1, a_2, a_3, \ldots a_t, \ldots)$ represent the probability of death for the insured for each time period t, given the best information *at the time of sale of the policy* ($t = 0$). Let $S_t = \sum_{\tau=t}^{\infty} a_\tau$ be the probability that the insured survives to period t. Let π be the per-period premium (per dollar of coverage) associated with the policy, which is determined by the mortality profile *at the time the policy was originally purchased* ($t < 0$). If $P(a)$ is the unit price a firm is willing to pay for life insurance to a consumer with mortality risk a, then present value of the expected profit from the purchase of the policy is:

$$(1)\quad E[Profit] = \sum_{t=1}^{\infty} (a_t - \pi S_t) b^t - P(a)$$

Where, $b = \dfrac{1}{1+r}$ and r is the cost of capital for viatical settlement firms. The first term in equation (1) represents the present value of expected revenue after the consumer's death (net of premium payments) and the second term represents the cash payment for the policy. In equilibrium, perfectly competitive firms will make zero profits and charge a price:

$$(2)\quad P(a) = \sum_{t=1}^{\infty} (a_t - \pi S_t) b^t$$

Equation (2) is the demand curve for life insurance given the mortality risk of the consumer and the cost of capital for firms. In equilibrium, prices are actuarially fair, and the demand curve is perfectly elastic.

Given this model for perfectly competitive firms it is easy to draw out the implications of minimum price regulation for the viatical settlements market. If the minimum price floor is set below the actuarially fair price then the price regulation will have no effect on market outcomes in a perfectly competitive market as price competition among viatical settlement firms will bid up the price to the actuarially fair price. On the other hand if the minimum price floor is set above the actuarially fair price firms will exit the market, as trading at the minimum price floor will result in losses for firms.

Thus, minimum prices above the actuarially fair price rule out certain viatical settlements that are otherwise appropriate and therefore reduce the likelihood of trades. Minimum prices below the actuarially fair price have no effect on the viatical settlements market. In the following two sections we describe our data and empirical strategy to evaluate the impact of price regulations on the viatical settlements market.

III. DATA

We evaluate the impact of minimum price regulation on the viatical settlements market using data from the HIV Costs and Services Utilization Study (HCSUS)—a nationally representative survey of HIV infected adults receiving care in the United States. This dataset is appropriate because it contains extensive information on a sample of terminally ill patients who constitute a large share of the viatical settlements market.

HCSUS is a panel study that followed the same set of patients over three interview waves. There were 2,864 respondents in the baseline survey, conducted between 1996 and 1997; 2,466 respondents in the first follow-up (FU1) survey, conducted in late 1997; and 2,267 respondents in the second follow-up (FU2) survey, conducted in 1998. The dataset has information on the respondents' demographics, income and assets, health status, life insurance, and participation in the viatical settlements market.

Questions about life insurance holdings and sales were asked in the FU1 and FU2 surveys but not in the baseline survey. Of the 2,466 respondents in FU1, 1,353 (54.7%) reported life insurance holdings. These 1,353 respondents are our analytic sample as they are the only patients at risk to viaticate. 344 of these respondents have missing values for at least one of the key variables—diagnosis date, health status—so we exclude them, leaving 1,009 respondents. In our remaining analytic sample, 132 (13%) respondents had sold their life insurance by the FU1 interview date, and an additional 33 respondents sold their life insurance between the FU1 and FU2 interview dates.

Table 1 compares summary statistics from the baseline interview of respondents who viaticated at some point in time with those who never did.[5] Viators are more likely than never-viators to be male, white, richer and older. They are also typically in poorer health, with lower CD4 T-cell levels at the baseline survey and more progressive HIV disease.

Table 2 provides the minimum price floors based on the NAIC model.[6] Eight states including Kansas, Louisiana, Minnesota, North Carolina, Oregon, Virginia, Washington and Wisconsin have adopted minimum price legislation based on the NAIC model.[7] More than 10% of the respondents in our analytic sample resided in states with minimum price regulation.

IV. Methods

A. Modeling the hazard of selling life insurance

Although HCSUS respondents report whether they sold their life insurance, they report neither the exact date of sale nor the quantity sold. Fortunately, because HCSUS respondents report whether they viaticated by FU1 and by FU2, we can determine the time at risk to viaticate. Given these data, we estimate an empirical model of the decision to viaticate that allows for time-varying covariates (including health status, assets, and income change over the course of the panel). Because we do not observe quantity sold, our focus is necessarily on the decision to sell at all.

There are three kinds of respondents—those who have viaticated by FU1, those who viaticated between FU1 and FU2, and those who never viaticate in the observation window. Each has a different contribution to the likelihood function. Let $\lambda(t)$ be the probability of not viaticating at time t given that the respondent has not viaticated in the preceding t-1 years. Time is measured starting from the year of diagnosis with HIV, or the viatical settlements market inception date—1988—whichever is earlier. The

[5] Including the 344 respondents who had at least one missing value has no appreciable effect on the summary statistics that we report in Table 1.
[6] See note 4, *supra*.
[7] National Association of Insurance Commissioners, Model Regulation for Viatical Settlements, (1997).

probability that a respondent never viaticated is $\prod_{t=1}^{T}\lambda(t)$, where T is years between the start and end of the observation window. Similarly the probability that a respondent viaticated by FU1 is $1-\prod_{t=1}^{T_1}\lambda(t)$ where T_1 is years between the start and the FU1 interview date. The probability that a respondent did not viaticate between the start date and FU1 but did viaticate by FU2 is $\prod_{t=1}^{T_1}\lambda(t)-\prod_{t=1}^{T_2}\lambda(t)$, where T_2 is years between the start and the FU2 interview date. Combining these three types of respondents gives the likelihood function:

$$(3)\qquad L=\prod_{i=1}^{N}\left\{D_{1i}\left[\prod_{t=1}^{T_1}\lambda_i(t)-\prod_{t=1}^{T_2}\lambda_i(t)\right]+D_{2i}\left[1-\prod_{t=1}^{T_1}\lambda_i(t)\right]+D_{3i}\left[\prod_{t=1}^{T}\lambda_i(t)\right]\right\}$$

where, i subscripts over the N respondents;

D_{1i} is a binary variable that indicates if respondent i viaticated between FU1 and FU2;

D_{2i} indicates if respondent i viaticated by FU1; and

D_{3i} indicates that respondent i never viaticated.

We model the hazard of not viaticating as,

$$(4)\qquad \lambda_i(t)=\frac{1}{1+\exp(\lambda_t^0+X_{it}\beta)}$$

where, X_{it} is a vector of covariates measured at time t, β is the vector of regression coefficients, and $\frac{1}{1+\exp(\lambda_t^0)}$ is the baseline logit hazard rate.

We maximize (3) to estimate the parameters λ_t^0 and β.

HCSUS respondents were sampled only at three discrete times. One major consequence of this sampling strategy is that we do not observe X_{it} at each point in time t, so we have no measures of patient health status or changes in assets between surveys. We use a step function approximation to impute values of X_{it}. For example, suppose a respondent is sampled at time points t_1, t_2, and t_3, and reports values for X_t of x_1, x_2, and x_3 at each of these time points respectively. We assign

$$X_t = \begin{cases} x_1 & \text{for } t \le t_1 \\ x_2 & \text{for } t_1 < t \le t_2 \\ x_3 & \text{for } t_2 < t \le t_3 \end{cases}$$

We include as covariates demographics, life expectancy, income, a binary variable for minimum price regulation and measures of the actuarially fair price and the minimum regulated price.

B. Estimating Life expectancy and the Actuarially Fair Price

We use the Cox proportional hazard model to estimate the life expectancy of HIV+ patients. Equations (5) and (6) give the hazard rate and survival function under the proportional hazard assumption:

(5) $$h(t) = h_0(t)\exp(X\beta)$$

(6) $$S(t) = \left[\exp\left(-\int_0^t h_0(u)du\right)\right]^{\exp(X\beta)}$$

Where t is the survival time; $h_0(t)$ is the baseline hazard function; X is a vector of explanatory variables and β is the corresponding vector of parameters for the covariates. We estimate the parameters $h_0(t)$ and β using maximum likelihood estimation.

However the parameters $h_0(t)$ are only estimated at times when failure occurs. To calculate life expectancy we need estimates of baseline hazards for all time periods. We predict the baseline hazard for non-failure times by fitting a linear trend to the estimated baseline hazard.

The estimated life expectancy of a respondent with hazard rate *h(t)* is simply the area under the survivor function:

(8) $$LE(h(t)) = \int_0^\infty \hat{S}(t)dt$$

The estimated actuarially fair price of a life insurance policy—net of per period estimated premiums $\hat{\pi}$—with \$1 face value is:

(9) $$AFP(h(t)) = \int_0^\infty \left[\hat{f}(t) - \hat{\pi}\hat{S}(t)\right]\exp(-rt)\,dt$$

Where $\hat{f}(t)$ is the estimated probability density function and r reflects the cost of capital for viatical settlement firms. This equation is the continuous time equivalent of the pricing equation (2).

We estimate per-period premiums, $\hat{\pi}$, assuming a constant mortality hazard evaluated at the time the policy was purchased (that is, when the insured person was healthy). Let λ be this constant hazard at the time of purchase. Let L be the life expectancy associated with this mortality hazard. The pricing equation for this actuarially fair life insurance policy assumes that the present value of premiums paid equals the present value of the life insurance benefit (again at the time of purchase). It is easy to show that this pricing equation implies $\pi = \frac{1}{L}$. We obtain estimates of L from the National Center for Health Statistics—Anderson (1999). Since we did not observe in our data when policies were purchased, we assumed that people bought them the year prior to contracting HIV disease.[8] Thus, our estimate of premiums paid is an upper bound on actual premiums paid. This implies our estimate of actuarially fair prices for viatical settlements—equation (9)—is a lower bound on the true actuarially fair price. Thus, we are effectively overestimating the size of the population on whom minimum price regulations are binding. If we were to assume zero premiums—that is, an infinite life span prior to contracting HIV disease—we would underestimate the size of this bound population. Our results with this underestimate of the bound population are qualitatively and quantitatively similar to the ones with the overestimate of the bound population, and are available upon request.

We estimated the cost of capital for viatical settlement firms as 16.52 percent per annum based on the data on the weighted average cost of capital of firms in the same standard industrial classification code (SIC code 6799) as viatical settlement firms.[9]

Covariates in the Cox proportional hazard models include indicator variables for level of CD4+ t-lymphocyte (CD4) cell count and stage of disease. When HCSUS was conducted, the two most important health status measures for HIV patients were CD4+ T-

[8] For the approximately 5% of the sample who contracted HIV after age 50, we assumed they purchased life insurance at age 50. Without this extra assumption, our calculations for premiums would exceed the viatical settlement value for two people in our population.
[9] Ibbotson Associates, Cost of Capital Quarterly, 1997 Yearbook. (1997)

lymphocyte cell count and the Center for Disease Control (CDC) definition of clinical stage. CD4+ T-cell count measures the function of a patient's immune system; depletion correlates strongly with worsening HIV disease and increasing risk of opportunistic infections.[10] While healthy patients have CD4 cell counts above 500 cells per ml., declines into lower clinically recognized ranges correlate with worsening disease. These ranges are: between 200 and 500 cells per ml., between 50 and 200 cells per ml., and below 50 cells per ml. There are three categories in CDC definition of clinical stage: asymptomatic, symptomatic, and AIDS.[11] Patients have AIDS if they manifest conditions such as Kaposi's Sarcoma, Toxoplasmosis, or other life threatening conditions on the CDC list. Symptomatic HIV+ patients manifest some conditions related to their infection, but not one of the AIDS defining conditions. A depletion in CD4 cells correlates strongly with the worsening of HIV disease and the risk of developing an AIDS-defining opportunistic infection.[12]

V. RESULTS

A. Life expectancy, actuarially fair prices, and price floors

Figure 1 shows the minimum prices and the average actuarially fair prices as a function of life expectancy. Minimum prices are based on legislated minimum prices of Table 2; hence the discrete jumps every six months until two years. Actuarially fair prices were calculated using equation (9). These calculations assume that viatical settlement firms could borrow funds at a cost of 16.5% per year.[13]

A well-designed pricing scheme would keep the minimum prices just above the actuarially fair price to minimize industry profits but ensure that trades can take place. If the price floors are set too low, the market might disappear completely. If they are too high, they will not be binding since low minimum prices will be bid away by demand-side competition. In fact, as shown in Figure 1, the mandated prices are lower than the

[10] A.S. Fauci et al. (eds.), Harrison's Principles of Internal Medicine, 14th edition. (1998)
[11] Centers for Disease Control and Prevention, 1993 Revised Classification System for HIV Infection and Expanded Surveillance Case Definition for AIDS among Adolescents and Adults. 269 J Am. Med. Assoc. 729-30. (1993).
[12] See note 10 *supra*.
[13] See note 11 *supra*.

actuarially fair price for very sick patients, suggesting these may not be binding. For patients with more than approximately 4 years of life expectancy, the minimum prices are higher than the actuarially fair price, so we expect very few trades for these HIV+ patients in relatively good health, as firms would make losses if they trade at the mandated minimum prices.

We predict life expectancy for our sample using equation (8). The results are shown in Table 3. The only covariates are CD4 count and disease stage. Patients with more advanced disease and lower CD4 counts have the lower life expectancy than patients with asymptomatic infection and higher CD4 counts. These life expectancy estimates are similar to those reported in the medical literature,[14] giving us confidence in our mortality model. A comparison of Table 3 with Figure 1 determines the patients for whom we expect the minimum prices to be not binding. The sickest patients—i.e., those with CD4 counts less than 50 cells per ml or for persons with AIDS and CD4 counts between 51 to 200 cells per ml—are not affected.

B. Settlement decision

Table 4 shows our unadjusted estimate of the effect of price floors on the likelihood of viatication. Of the 1009 respondents in our sample, 123 (12 %) reported residing in states with minimum price regulation. Of these 123 respondents, 73 (59%) had actuarially fair price greater than minimum price at the time of baseline interview. These 73 respondents (treatment group) constitute the group for which minimum price regulation should be binding and should therefore reduce the likelihood of sale of life insurance. The remaining 936 respondents (control group) either resided in states with no minimum price regulation or resided in states with regulations that are non binding (i.e., they had life expectancies exceeding four years).

Of the 73 respondents in the treatment group, 6.8% sold their life insurance policies. By contrast, 17% of the respondents in the control group sold their life insurance policies. This difference is statistically significant at the 95 percent confidence level. These results are clearly consistent with the story that firms in regulated states are

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[14] K. Freedberg , *et al*. The Cost Effectiveness of Combination Antiretroviral Therapy for HIV Disease, 344 N. Engl. J. Med., 824 – 831 (2001).

unwilling to buy policies from the relatively healthy, as they would make losses if they bought policies at the mandated minimum prices.

Table 5 reports the average hazard ratios at $t = 1$ and baseline hazard rates for 4 different specifications of the empirical model reported in equation (3). We average the hazard ratios for each covariate across all individuals in the sample as they depend not only on the regression coefficient associated with the covariate but also on the values of the other covariates. Appendix 1 specifies our methodology for computing the hazard ratios and their standard errors.

The second column (Model 1) in Table 5 reports the results for the simplest empirical model needed to test the prediction from the competitive model. The results show that consumers faced with a binding price regulation are 0.35 times less likely to viaticate than consumer in unregulated markets or consumers in regulated markets but with non binding regulation. Despite the small sample size in the treatment group, the effect size is significant at the 95 percent confidence level.

Model 2 in Table 5 adds demographic variables to the explanatory variables in Model 1. We also add marital status and the number of children as additional explanatory variables as measures of the bequest motives of the respondents. Respondents who are younger, married and have more children are less likely to viaticate. Whites have significantly higher hazards of viaticating than do blacks, hispanics, and respondents of other races. As was true in Model 1, the results of this model conform to the prediction that price regulation restricts demand for the life insurance policies of the relatively healthy.

Model 3 adds indicator variables for income and employment to measure the liquidity constraints facing respondents. Respondents who are employed and who have higher incomes should be less likely to viaticate. There are no statistically significant differences in the likelihood of viatication between respondents with higher incomes or between the employed and unemployed. These results also support the story that binding price regulation lowers the likelihood of viatication.

In Model 4 we add life expectancy of the respondents as an additional covariate. Although in competitive markets with actuarially fair prices there should be no correlation between mortality risk and the likelihood of viaticating,[15] we add life expectancy as a proxy for unobserved need for liquidity to finance medical expenditures. Therefore according to our hypothesis respondents with low life expectancy should be more likely to viaticate, as they might finance increased medical expenses by selling their life insurance policy. The results show that respondents with higher life expectancy are significantly less likely to viaticate. The point estimate from this model also suggests restricted demand for policies of respondents for whom price regulation is binding, though it is statistically significant at the 90 percent confidence level only.

Table 6 shows a calculation of the degree of welfare loss if all states were to implement minimum price regulation. The HCSUS data represents approximately 231,400 HIV+ adults who received care in the first 2 months of 1996.[16] Our analytic sample represents an estimated 123,200 of these HIV+ adults who owned life insurance. Of these patients, an estimated 66,859 patients would face binding price regulation if all states were to implement minimum price regulation. An estimated 11,333 (17 %)[17] of these patients would have sold their life insurance policies if these states had not implemented minimum price regulation. The average face value of the life insurance holdings of these patients were $78,895 and they could sell their policies in the viatical market and obtain about 44 percent of the face value in immediate cash payment. This implies that if price regulation were implemented in all states it would rule out transactions worth approximately $484 million representing a welfare loss of about $242 million[18].

VI. IMPLICATIONS

In a competitive market, price regulation in the viatical settlements market rules out certain trades that are otherwise appropriate. The regulatory scheme imposed by most states also discriminates against the relatively healthy HIV population by setting

[15] J. Cawley and T. Philipson, An Empirical Examination of Information Barriers to Trade in Insurance, 89 Am. Econ. Rev. 827-845. (1999)

[16] S. Bozzette *et al.*, The Care of HIV-Infected Adults in the United States, 339 N. Engl. J. Med. 1897-1904 (1998).

[17] This is the percentage of respondents who faced non-binding price regulation and sold life insurance.

[18] This calculation assumes that the supply curve of viatical settlements is linear with an intercept at the origin. The welfare loss is the loss in producer surplus represented by the area of the triangle between the perfectly elastic demand curve and a linear supply curve.

price floors that are binding only with high life expectancy. This imposes a daunting prospect for HIV+ patients with life insurance but limited liquidity. They would like to finance treatment by selling their life insurance in the early stages of infection—thereby forestalling progression to AIDS and eventual mortality—but regulatory restrictions require them to let their health deteriorate before they can find a buyer of their policy.

The welfare losses from these restrictions could be large if they continue to promulgate. Indeed, our estimates of welfare loss are conservative since they exclude the elderly, the disabled, and patients with other illnesses such as cancer. They also exclude the effects of these regulations on the potentially much larger market for accelerated death benefits. Even if only a small fraction of the $10 trillion in life insurance at risk of being cashed out with accelerated death benefits are actually prevented, the welfare losses are likely to be enormous, and entirely unnecessary. These welfare losses are large enough to encourage black markets—already there are reports of fraud by unregulated companies like the "The Grim Reaper" thriving in this market.[19] On the other hand, as Coase puts it, "…there have been very few controls which have not been modified to take [economic] forces into account, or even abandoned, so that market forces have free sway."[20]

[19] Gloria Grening Wolk, Cash for Final Days: A Financial Guide for the Terminally Ill and their Advisors, (1997).
[20] R.H. Coase., Essays on Economics and Economists (1994), at p.55.

Appendix 1: Monte Carlo Computation of Hazard Ratios

We use Monte Carlo simulations to calculate the hazard ratios, hazard rates and standard errors reported in Table 4. Let $\mu_{est} = \begin{pmatrix} \beta_{est} \\ \lambda^0_{est} \end{pmatrix}$ be the maximum likelihood estimates of $\beta = (\beta_1, \beta_2, ...\beta_k)$ (where k is the number of covariates) and $\lambda^0 = (\lambda^0_1, \lambda^0_2, ...\lambda^0_9)$ from equation (17), and let Σ_{est} be the estimated variance covariance matrix of μ, which is asymptotically distributed multivariate normal.

In each iteration of the Monte Carlo simulation, we draw a random vector of regression coefficients, $\mu^{(i)} = (\beta^{(i)}, \lambda^{0(i)})$ from $N(\mu_{est}, \Sigma_{est})$, where i indexes over the iterations. Using this randomly drawn $\mu^{(i)}$ we calculate an average hazard ratio for each dichotomous covariate:

(A-1) $$hazard\ ratio_{i,k} = \frac{1}{N}\sum_{j=1}^{N} \frac{1-\lambda_j\left(1 \mid X_k = 1, X_{k+1} = 0, \ldots X_{k+m} = 0, \mu = \mu^{(i)}\right)}{1-\lambda_j\left(1 \mid X_k = 0, X_{k+1} = 0, \ldots X_{k+m} = 0, \mu = \mu^{(i)}\right)}$$

where, j subscripts over the N respondents in the data set, and
$(X_k, \ldots X_{k+m})$ is a mutually exclusive set of dichotomous covariates.

For continuously measured covariates we calculate the average hazard ratio using:

(A-2) $$hazard\ ratio_{i,k} = \frac{1}{N}\sum_{j=1}^{N} \frac{1-\lambda_j\left(1 \mid X_k = X_k + \theta, \mu = \mu^{(i)}\right)}{1-\lambda_j\left(1 \mid X_k = X_k, \mu = \mu^{(i)}\right)}$$

where, θ is an arbitrary offset. For the hazard ratio corresponding to age, we set $\theta = 5$ years.

Also, we calculate the baseline hazard of viaticating at each time period,

(A-3) $$baseline\ hazard\ rate_i(t) = \frac{\exp\left(\lambda^{0(i)}_t\right)}{1+\exp\left(\lambda^{0(i)}_t\right)} \quad t = 1 \ldots 9 \text{ years.}$$

We repeat 10,000 iterations. Finally, we calculate the mean and standard deviation of (A-1)-(A-3) over all the 10,000 iterations, which we report in Table 5.

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Table 1: Demographics at Baseline of Viators vs. Non-viators

Variables	Entire Sample N = 1009	Viators N = 165	Non-Viators N = 844
Age	35	37	35
Male	81%	88%	80%
White	59%	78%	56%
Black	24%	16%	26%
Hispanic	11%	5%	12%
Monthly Income			
< $500	15%	13%	16%
$501 - $2000	41%	41%	40%
> $2000	44%	46%	44%
Disease Stage:			
Asymptomatic	9%	9%	9%
Symptomatic	51%	38%	54%
AIDS	39%	53%	37%
CD4 T-cell levels:			
< 50 cells per ml	12%	15%	11%
50 - 200 cells per ml	25%	41%	22%
201 - 500 cells per ml	42%	32%	44%
> 500 cells per ml	21%	13%	23%

Table 2: Mandated Minimum Prices as a Percentage of Face Value

Life Expectancy	Minimum Price
Less than 6 months	0.80
6 to 12 months	0.70
12 to 18 months	0.65
18 to 24 months	0.60
Greater than 24 months	0.50

Table 3: Life expectancy in Years by CD4 level and Stage of Disease

	Clinical Stage of Disease		
CD4 Level	Asymptomatic	Symptomatic	AIDS
CD4 > 500	11.56	8.77	6.20
CD4 201 - 500	9.90	7.46	5.23
CD4 51 - 200	5.03	3.68	2.48
CD4 < 50	2.39	1.69	1.09

Table 4. Regulatory Status and Likelihood of Viaticating

	Non-Binding Regulation			
	Unregulated States	Regulated States	Total	Binding Price Regulation*
No. of policyholders	866	70	956	53
Percent Sold	16%	28% (1)	17% (2)	6.8% (3)

Hypothesis Tests:

Null Hypothesis	t -stat	p-value
Ho: (3) - (1) = 0	-2.28	0.020
Ho: (3) - (2) = 0	-3.30	0.001

*Regulations are binding for those patients for whom the actuarially fair price is less than the minimum price.

Table 5: Results of empirical models of the hazard of viatication

Variables	Model 1 Haz. Ratio (s.e.)	Model 2 Haz. Ratio (s.e.)	Model 3 Haz. Ratio (s.e.)	Model 4 Haz. Ratio (s.e.)
Binding Price Regulation	0.348 (0.232)	0.337 (0.223)	0.352 (0.240)	0.421 (0.275)
Male	--	1.203 (0.292)	1.173 (0.290)	1.149 (0.282)
Black#	--	0.617 (0.114)	0.620 (0.118)	0.637 (0.120)
Hispanic#	--	0.327 (0.115)	0.336 (0.124)	0.337 (0.121)
Other Race#	--	0.487 (0.231)	0.482 (0.232)	0.437 (0.209)
Age	--	1.193 (0.053)	1.178 (0.053)	1.180 (0.054)
Married	--	0.955 (0.194)	0.941 (0.192)	0.923 (0.188)
Number of Children	--	0.962 (0.059)	0.957 (0.060)	0.968 (0.059)
Income $500 -2000‡	--	--	0.948 (0.221)	0.888 (0.202)
Income > $2000‡	--	--	1.126 (0.270)	1.097 (0.253)
Employed Full or Part time	--	--	0.799 (0.116)	0.974 (0.151)
Life Expectancy	--	--	--	0.887 (0.132)

Reference Category: White; ‡ Reference Category: Income < $500

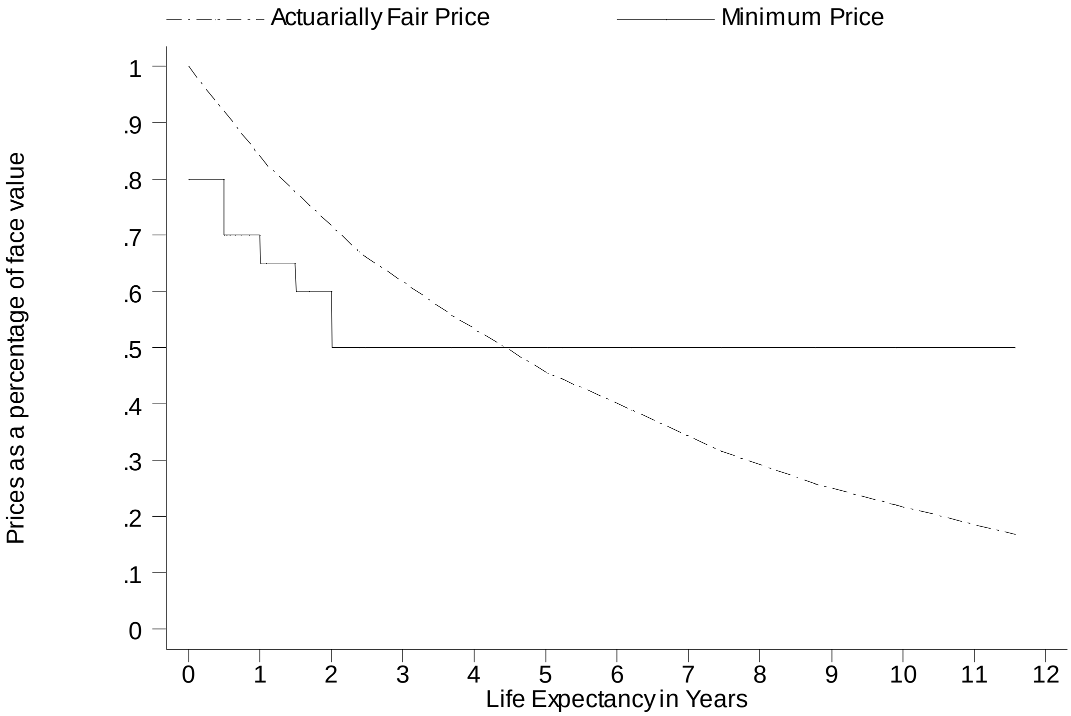
Table 6: Welfare Loss If All States Enacted Minimum Price Regulation

Row	Label	Quantity
1	Estimated HIV+ patients with binding price Regulation	82,074
2	Percent Who would have viaticated with no regulation	17%
3	Number of trades blocked—Row(1) X Row(2)	13,953
4	Avg. face value of life insurance	$78,895
5	Avg. actuarially fair price as percentage of face value	44%
6	Avg. Price of trade Blocked—Row(4) X Row(5)	$34,753
7	Total Value of trades blocked—Row(3) X Row(6)	$484,912,062
8	Welfare Loss	$242,456,031

Figure Legends

Figure 1: Minimum Prices and Actuarially Fair Prices as a Function of Life Expectancy

Figure 1: Minimum and Actuarially Fair Prices as a Function of Life Expectancy



Note. Actuarially fair prices are computed using equation (9). Minimum prices are from Table 2.